Fall 2016

Hidden Markov Model based non-intrusive load monitoring using active and reactive power consumption

Paulomi Nandy

HIDDEN MARKOV MODEL BASED NON-INTRUSIVE LOAD MONITORING USING ACTIVE AND REACTIVE POWER CONSUMPTION

By

PAULOMI NANDY

A MASTER'S THESIS

Presented to the Faculty of the Graduate School of the

MISSOURI UNIVERSITY OF SCIENCE AND TECHNOLOGY

In Partial Fulfillment of the Requirements for the Degree

MASTER'S IN ELECTRICAL ENGINEERING

2016

Approved by

Dr. Jonathan W. Kimball, Advisor
Dr. Mehdi Ferdowsi
Dr. Hank Pernicka

ABSTRACT

This work presents a residential appliance disaggregation technique to help achieve the fundamental goal in Non-Intrusive Load Monitoring (NILM) problem i.e. simple breakdown of energy consumption based on the appliance type in a household. The appliances are modeled using Hidden Markov Model by utilizing both their active and reactive power consumption data. The data was recorded by attaching Power Standards Lab PQube measurement device to the appliances. Granularity of the power readings of the disaggregated appliance matches with that of the reading collected for individual device. The accuracy of the model is compared with other models developed using only active power consumption of the appliances. The results using the proposed method are more effective and are found to predict a better output sequence for the appliances compared to model using only active power for modeling loads.

ACKNOWLEDGMENTS

First and foremost I would like to recognize Dr. Jonathan Kimball, my advisor and teacher, who supported me throughout my research and academics with his patience and knowledge. It has been a great experience working under his guidance. I would also like to thank Dr. Mehdi Ferdowsi and Dr. Hank Pernicka for serving on my committee and for being such a great source of inspiration. This work was funded in part by the National Science Foundation under award 1406156.

I would also like to thank all my lab mates for their valuable contribution towards my research. I would like to thank Jacob Muller for his continuous support and inspiration over the course of my research. I would also like to thank my lab mates and friends, Maigha Garg, Phani Marthi, Jaswant Vutukury, Aditi Pachal, Devdatt Chattopadhyay, Kaustav Ghosh, Kaustav Roy, Ayush Sengupta for their support throughout my course of Master's Degree and making my stay in Graduate school a memorable one. A special thanks to Bhanu Prashant Reddy Baddipadiga for always believing and being patient with me.

I owe a special thanks to my father and mother and my late grandmother who have taught me the important values in my life and my brother for his unconditional love and support. I would also like to thank Mark Pannell and Jennifer Pannell for their constant love and support.

TABLE OF CONTENTS

LIST OF FIGURES

Page

LIST OF TABLES

1 INTRODUCTION

Non-intrusive Load Monitoring (NILM) was defined by George W. Hart [1] in 1992 as determining the energy consumption of individual appliances turning on and off in an electrical load, based on detailed analysis of the current and voltage of the total load. This method was earlier developed to simplify the energy consumption data collection by the utilities. The process is called non-intrusive since each appliance does not have to be monitored and thus reducing the intrusion into the consumer's property. The consumer's power consumption data is extremely crucial and valuable to both utility and users to help understand their power consumption trend and generate enough electricity to meet the consumers demand. The NILM system can be used to determine the time of use of an appliance and allows the occupants to know the potential saving by using the appliance at off peak hours. In an event of faulty appliance the unusual energy consumption of an appliance can be detected and replaced. NILM can also be used for security purpose where it helps the owner know what appliances are turned 'ON' in the apartment.

The aim of this work is to develop a NILM method that provides a better assessment of the appliances operation by using both active and reactive power consumption. Research work focuses on ways to investigate how machine learning can be used in development of NILM method using both active and reactive power. This research effort will help disaggregate use of combined house appliances into individual appliances.

The problem is broken down in to three stages: In the first stage, individual load characteristics are studied and the models are trained based on individual characteristics. In the second stage the models are combined to form a composite model using individual trained model. The combined model had all the possible state transition and observation probabilities of individual appliances. In the last stage a mathematical algorithm is used to predict the best state sequence using both active and reactive power consumption for each appliance. The proposed prediction technique was tested against the previous research which uses only active power for modeling and disaggregating the loads. In last section we present the results and the success rate of the proposed approach.

2 BACKGROUND

The main goal of NILM using Hidden Markov model (HMM) is to provide a model structure for detecting, storing and recognizing the recurring power consumption pattern of a house hold. The monitoring system should be able to identify individual appliance by observing the power consumption. The system considered in this study has known set of devices. While this might limit the application of the proposed method it still can be used in various fields where the systems are predesigned for example, satellite, factories, data-centers, residential application [2-4]. These systems are premeditated and designed, thus extensive device level data is already available. Several methods have been unified for the process which includes factor analysis, principle component analysis, mixture of Gaussian clusters, vector quantization, Kalman filter model, and HMM. The underlying principle behind the NILM is the same. For load recognition, a model of the appliance is required which can be used for discrete time and continuous valued data, so as with HMM.[5].

Research efforts focus on NILM methods using HMM to describe electrical system.[6-8] The interest in HMM is also motivated by the simplicity of basic load modeling. It is an efficient and easy method for parameter estimation using Baum-Welch method and Viterbi Algorithm for inference [2, 9]. Trained device models are used to infer the most likely sequence for a device given a set of measurement. HMM can be used accurately to predict device behavior using low frequency (≤1 Hz) measurements. This is especially useful since HMM based NILM method could be implemented using existing measuring devices and also+ reduces the overall volume of measurement data collected.[10]

While NILM can be implemented in numerous ways but they all have the same basic method. The devices need to be mathematically modeled using their load profile characteristics. This includes their power consumption and states of operation. The load profiles of all the devices are combined to form one composite load model. And lastly the individual loads are disaggregated or separated using their load characteristics. The way each process is done differs and can produce different results [11, 12]. Data acquisition is an integral part of NILM. Data use can be either collected at the point of operation or from the main electrical panel outside the building or resident. Non-intrusive monitoring is a simple hardware but complex software process as explained by Hart[1]. Complex software is required to analyze the appliance signal. Thus for; this reason non-intrusive load monitoring is considered as a cost effective trade-off, which is a major advantage of NILM.

2.1 INTRUSIVE LOAD MONITORING

Intrusive load monitoring or distributed monitoring is more accurate method of measuring energy consumption of an appliance. This process requires configuring multiple sensors and installing them on individual appliance. This is both expensive and a tedious process. Intrusive load monitoring is further categorized as electrical sub-metering and appliance tagging.

Electrical sub-metering is monitoring energy consumption of individual appliance. Sub-metering individual appliance helps the user to see the energy use and monitor the performance of the appliances, thus creating an opportunity of energy saving. Intrusive load monitoring is costly and time consuming process making this approach impractical.

Appliance tagging is a process in which each appliance has a RFID tag that emits a signal when the appliances turn on and off. These signals are gathered at a central hub that estimates each appliance's power consumption. Previous research has demonstrated the use of transmitting an RFID signal through the main circuit to a central recorder in order to uniquely identify appliances. However, each appliance is customized in addition to the installation of a central signature detector. As with electrical sub metering the installation time and cost per household is considerable and is therefore not considered by the researchers [1].

2.2 NON INTRUSIVE LOAD MONITORING

NILM system is referred to the process of monitoring an electric circuit that consists of a number of appliances switching on and off independently [1].In NILM system the appliance information is obtained at main breaker level. This is a more cost-effective method of gathering load data compared to intrusive load monitoring. The NILM system monitors the total load, checks for certain appliance "signature" that provides information about the state which contribute to the total load [13, 14].

2.3 ANALYSIS OF APPLIANCE

In this work we have only considered non-intrusive method with steady state signatures. The appliances can be categorized into three main types. The first category of appliance is, with two states of operation (ON/OFF). For example, lamp, toaster, Electric heater. The second category is the multi state appliances with finite states of operation and is usually referred to as Finite state Machines (FSM). These include washing machine, refrigerator and TV. The operating patterns are repeatable and can thus be used for disaggregation. The last category is the appliances which have variable power consumption with no fixed number of states. These are called Continuous Variable Devices (CVD). Power drills and lights with dimmers are such appliances and it is difficult to disaggregate these appliances. The states are assigned based on the modes of operation. Figure 2-1 shows the finite state machine with energy consumption. The circle shows the states which are defined by the operation. The direction of the arrow shows the transitions occurring in the machine. The figure only shows the steady state real power signature. Figure 2-1(a) is a finite state model of a machine with two states, ON and OFF with 1000W power consumption. Figure 2-1(b) shows a refrigerator with defrost mode of operation.

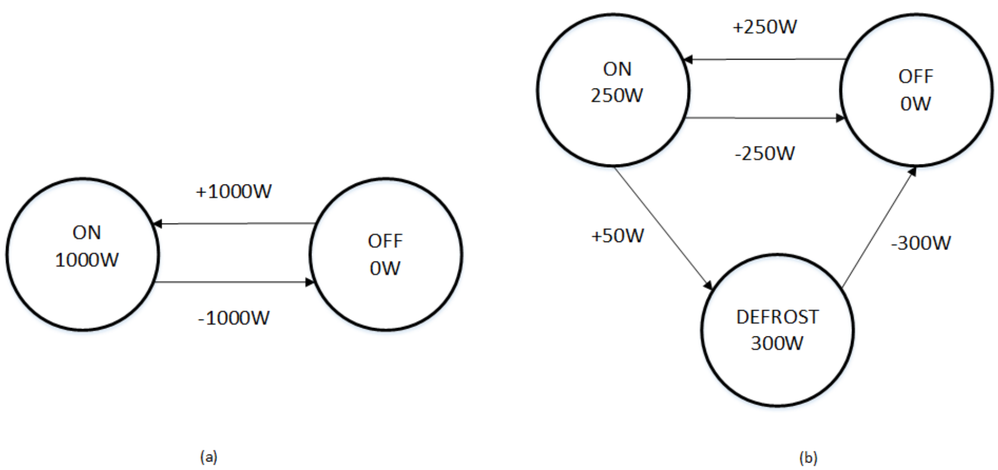

Figure 2-1 Finite State appliance model: (a) generic 1000W two-state appliance, (b) refrigerator with defrost state

Steady-state signatures are derived from the different steady state properties. Operating states are calculated as the difference between the operating levels of the connected states [1, 15]. Sampling rates and the process required to detect the step changes in power consumption of an appliance are far less complex than those required to capture and analyze transient spikes. The change in power or the transition of an appliance from one state to next is called an *event*. It helps us understand the state changes in an appliance in a time span.

Each appliance has their unique energy consumption pattern which is often referred to as "load signatures" which helps to disaggregate the appliances from one another. The iden10tification of various appliances from the composite model mainly depends on their unique load signatures which help characterize the appliances.

2.4 HIDDEN MARKOV MODEL

Hidden Markov model is a statistical model which follows Markov process. In hidden Markov process the states are directly not visible, but the output depends on states. Each state has a probabilistic distribution over possible output token. Thus, the sequence of the output gives us information of the sequence of states the system transitions through.[9] Both the probability of the hidden process transition to a new state and the probability of the output being observed, satisfy Markov property of: they are conditional only on the current state and are independent of the states and output at all other times.[16].

The appliance we want to model has N states. State of an appliance is often defined with a human insight into the appliance's pre-defined nature and might be somewhat related to the power consumption at each state. For example, an oven has two states, the off state as state one or S_1 and the on state or when the resistor is on and can be designated as state two or S_2 as shown in Figure 2-2.

Each state will have distinct observation i.e. discrete energy consumption. The observations are the active and reactive power consumed by the appliance.

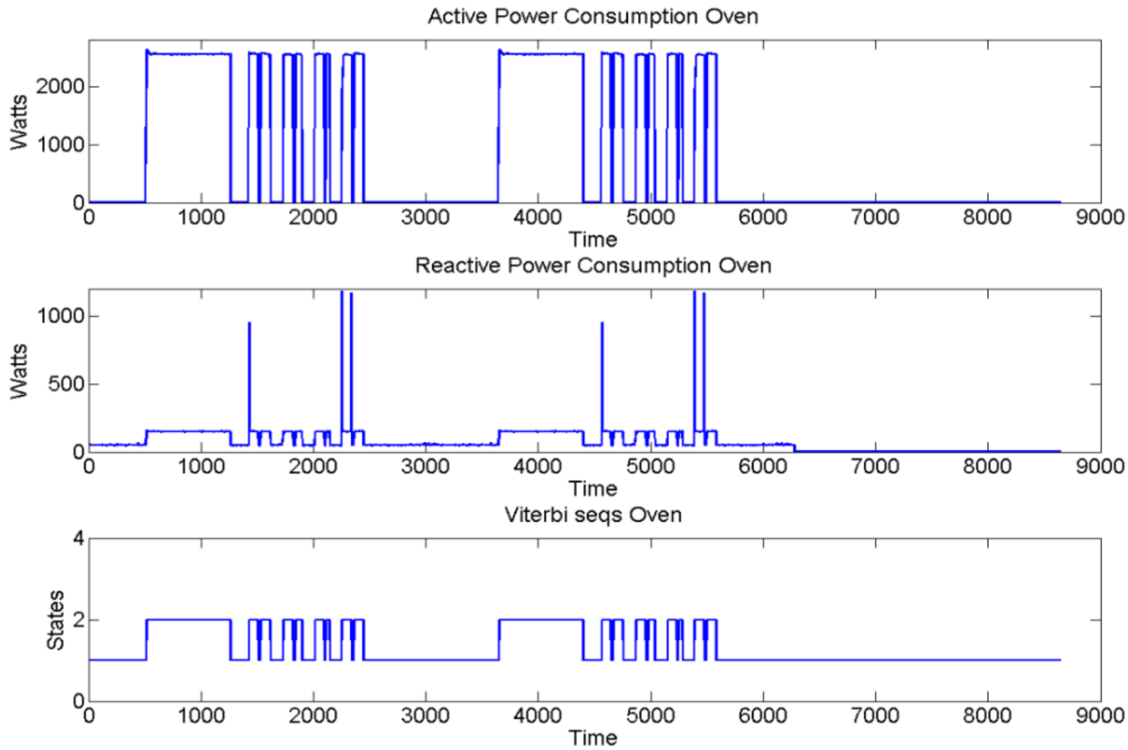

Figure 2-2 Active and Reactive power consumption of oven with corresponding state sequence

Hart suggests using steady state variation of active and reactive power to detect the status of the load. Each load in the house consumes a unique value of active and reactive power. When there is any change in active and reactive power, this change corresponds to a particular load. The observation is then noted as a change in state of the appliance [17].

For example, when the oven as seen in Figure 2-2 is in state one, the observation or active and reactive power consumption is 0W and 50VAR respectively (as shown in Table 2-1), whereas in state two it goes to 2kW and 200VAR respectively. The energy consumption can be observed over a length of time T. This result in an observation sequence which can be expressed as (1) and (2).

$$O_{active} = \{O_1, O_2, O_3, \ldots O_k\}, \tag{1}$$

$$O_{reactive} = \{O_1, O_2, O_3, \ldots O_k\}, \tag{2}$$

This sequence corresponds to sequence of states,

$$Q = \{q_1, q_2, q_3 \ldots, q_k\},\ q_k \in \{S_1, S_2, S_3 \ldots S_N\}, \tag{3}$$

Where S_1 through S_N are the device states.

Table 2-1 State and Power consumption of oven

Model state description	State	Active Power Consumption	Reactive Power Consumption
Oven off/resistor element off	S_1	0W	50VAR
Oven on/resistor element on	S2	2kW	200VAR

HMM is composed of transition probability matrix, observation probability matrix and initial state probabilities. Transition probability matrix of an appliance is denoted by ***A*,** and defined as the probability of transition from one state to the next from a particular state.

$$\mathbf{A} = \{a_{ij}\} \tag{4}$$

$$a_{ij} = \frac{\text{Expected number of transitions from state } S_i \text{ to state } S_j}{\text{Expected number of transition from state } S_i} \tag{5}$$

$$= P\left[q_{t+1} = S_j \mid q_t = S_i\right] \quad 1 \le i, j \le N, \tag{6}$$

where, N is number of state of an appliance in a system. $a_{ij} > 0$ for all i,j. The observation matrix is denoted by $\boldsymbol{\varphi}$**,** and is the probability of getting the observation given at that state.

$$\varphi_i(O_k) = P[O_k \ q_k = S_i] \tag{7}$$

In the above equation $\varphi_i(O_k)$ is the density function with O_k can be any real positive value. When observation values are discrete valued where $O_k \in \{v_1, v_2, v_3, \ldots, v_M\}$ where v_1 through v_M are discrete output symbols. Then in this case, $\varphi \in \mathbb{R}^{NxM}$ of elements of φ_{ij}

$$\varphi_{ij}(O_k) = P[O_k = v_k S_k = q_i], \tag{8}$$

And finally, the initial state probabilities is expressed by

$$\pi_i = P[q_1 = S_i] \ ,1 \le i, j \le N \tag{9}$$

For complete parameter set of an appliance consists of three probability measure $\boldsymbol{A}$, $\boldsymbol{\varphi}$, $\boldsymbol{\pi}$ and can be denoted as

$$\lambda = (A, \ \varphi, \ \pi) \tag{10}$$

In this work, the initial probability is assumed to be $q_1=S_1$ with probability of 1. With observation sequence O and model parameters A, φ, π, we use the Viterbi algorithm to compute the most likely corresponding sequence of state. In our case since we consider both active and reactive power for each model thus our model consists of two observation matrix, one corresponding to active power and another for reactive. For most appliances the active and reactive power are closely related. As we see in Figure 2-3 as the active power increases or decreases so does the reactive power.

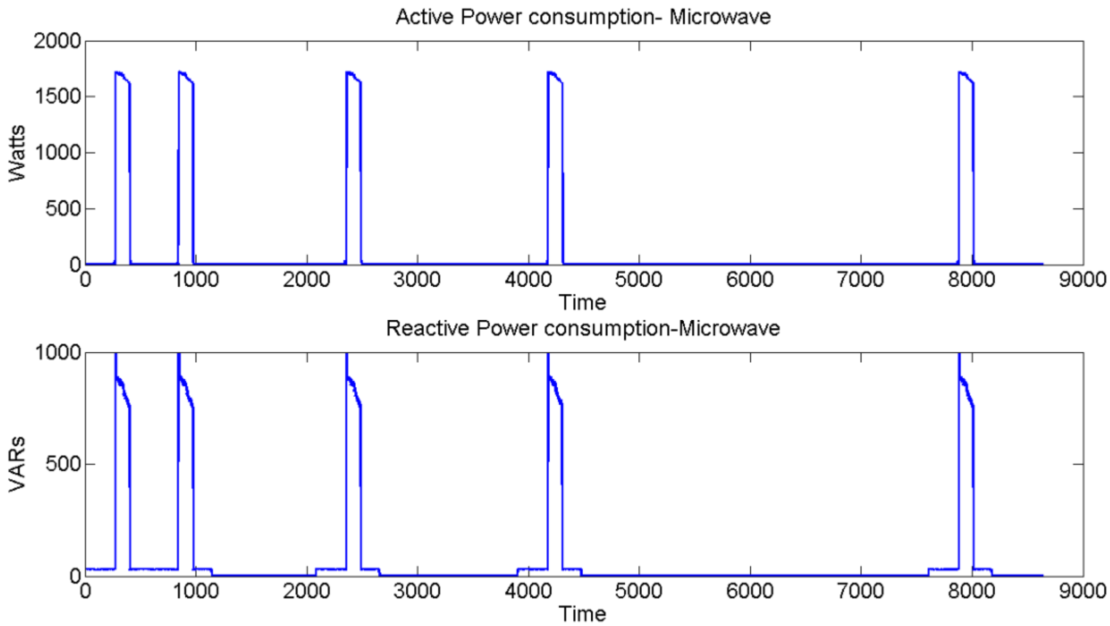

Figure 2-3 Active and Reactive power consumption of a microwave

Thus we have two different observation matrices but one transition matrix, as the transition from one state to the next is same for both the active and reactive observation sequence. This slightly changes our appliance model to

$$\lambda' = \left(A,\ \varphi_{active}\ , \varphi_{reactive},\ \pi \right) \qquad (11)$$

Figure 2-4 explains how the transition, observation probability matrix and the different components come together to form a model for a refrigerator. The black lines in the figure show all the transition probability. When the refrigerator is state 1 which is the 'OFF' state which has the probability of 99% of staying in state1 and 1% probability of turning 'ON' or transition to state 2. Similarly when in state 2 there is 80% probability of staying in state 2, 20% probability of going to state 3. The red lines show all the observation probability. When the refrigerator is in state 1 has 100% probability of having 0W and 0 VARs of power consumption. Similarly state 2 has the highest probability of having 300W and 130VARs power consumption with 60% and 80% probability respectively.

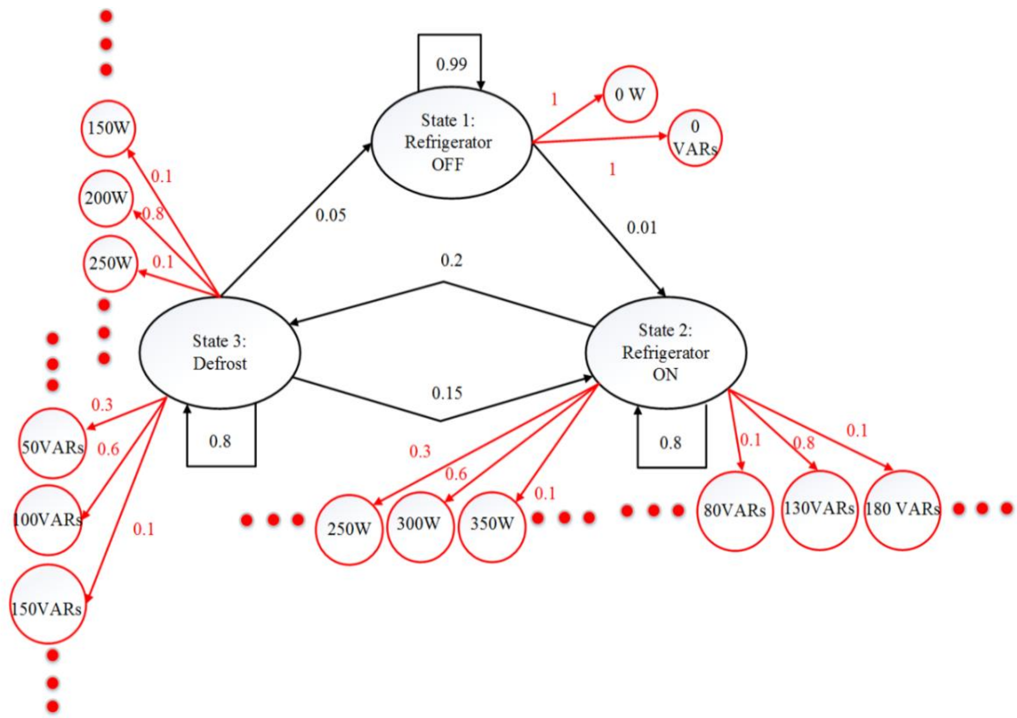

Figure 2-4 Refrigerator model with transition and observation probability matrix

The model is then used to find the most likely sequence by using the observation probability matrices and the transition matrix. Viterbi algorithm is a dynamic programming algorithm for finding the most *likely* sequence of hidden states also known as the Viterbi path. Viterbi path is the best state sequence for a given observation sequence. The idea is to process the observation sequence from left to right filling out in a trellis format. Each cell in the trellis represents the probability that the Markov Model is in state *j* after seeing the first *t* observations and passing through the most probable state sequence Q, given the A, φ_{active} ,$\varphi_{reactive}$, π. Thus each cell can be expressed as

$$v_t(j) = \max_{q_0,q_1,\ldots q_{t-1}} P(q_0, q_1, \ldots q_{t-1}, O_1, O_2 \ldots O_t,\ q_t = j|\lambda) \tag{12}$$

The most probable path is represented by the maximum over all previous possible state sequence $\max\limits_{q0,q1,\ldots qt-1}$ .Each cell in trellis is filled recursively. Given that we already computed the probability of being in every state at *t-1*, we take the most probable of the extensions of the path that lead to the current cell. For a given state q_j at time t, the value v_i is computed by multiplying the previous Viterbi path probability from previous step, transition probability and the state observation likelihood

$$v_i(j) = \max_{i=1}^{N} v_{i-1}(i) a_{ij} \varphi_{activej}(O_i) \varphi_{reactivej}(O_i) \quad (13)$$

Thus Viterbi algorithm helps to compute both the probability and most likely states sequence. In implementation, the natural log of probabilities is used instead so that they may be added instead of multiplying. This improves numerical conditioning. The best state sequence is obtained by keeping track of the hidden states that led to each state and then at the end back tracing the best path to the beginning.

3 PROPOSED DISAGGREGATION TECHNIQUE FOR NILM

This section focuses on the application of Hidden Markov model for appliance modeling and disaggregation using the data collected using smart meter. First we individually model each appliance using their active and reactive power consumption obtained from the meter. Then each model is combined to form a combined Hidden Markov Model. Using the novel appliance disaggregation technique each appliance is disaggregated into individual appliance.

3.1 MODELING INDIVIDUAL LOAD

To build a non-intrusive solution for load monitoring, it is necessary to understand the range of appliance the system needs to disaggregate. Individual appliance load modeling is done as mentioned in [18]. The active and reactive power consumption of the appliances is collected using Power Standards Lab PQube measurement device. The data is converted into observation sequence by binning the power level. The input of each bin is a range of power values with each bin output corresponding sequence of observation based on bin size. Similar power consumption in a load profile is assigned a single state or value.

States are different modes of operation of a load. Taking the same example of the oven as shown in Figure 3-1, the ‘OFF’ state will be assigned state 1 and will have observation falling in bin zero, the on state or state2 will have higher bin compare to off state. If the appliance has observation falling beyond the current state then the observation area allocated to a new bin. Thus appliance with more states will have states with higher bin with each state. Modeling of individual load appliance is carried out. The transition matrix which contains the transition probability from state *i* to state *j* from state *i*. Similarly Figure 3-2 and Figure 3-3 show the corresponding states for microwave and HVAC system. The output observation matrix is the observation probability of φ_{ij} is the probability of finding an observation O_k at state *i*. For each individual appliance the observation and transition matrix are computed.

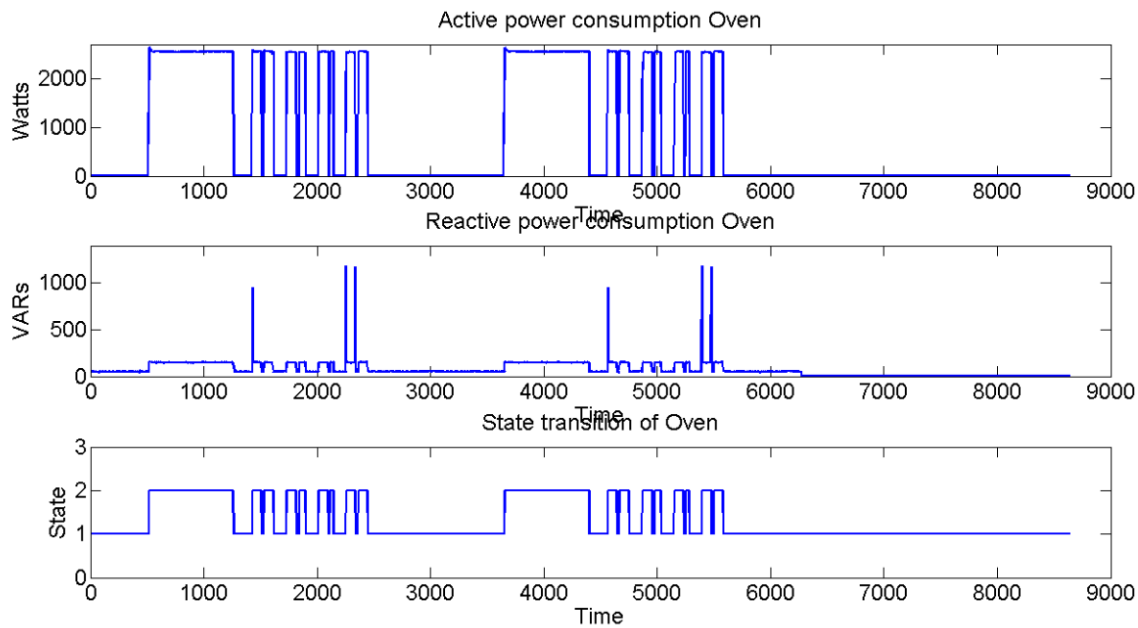

Figure 3-1 Active and Reactive power consumption of oven with Viterbi sequence

Since we are working with both active and reactive power we have two observation matrices with one transition matrix. The transition and the observation matrices are given as input to the Viterbi algorithm. The Viterbi algorithm gives the optimal state sequence of the appliance. The pseudo code for Viterbi algorithm is given in the Appendix A.

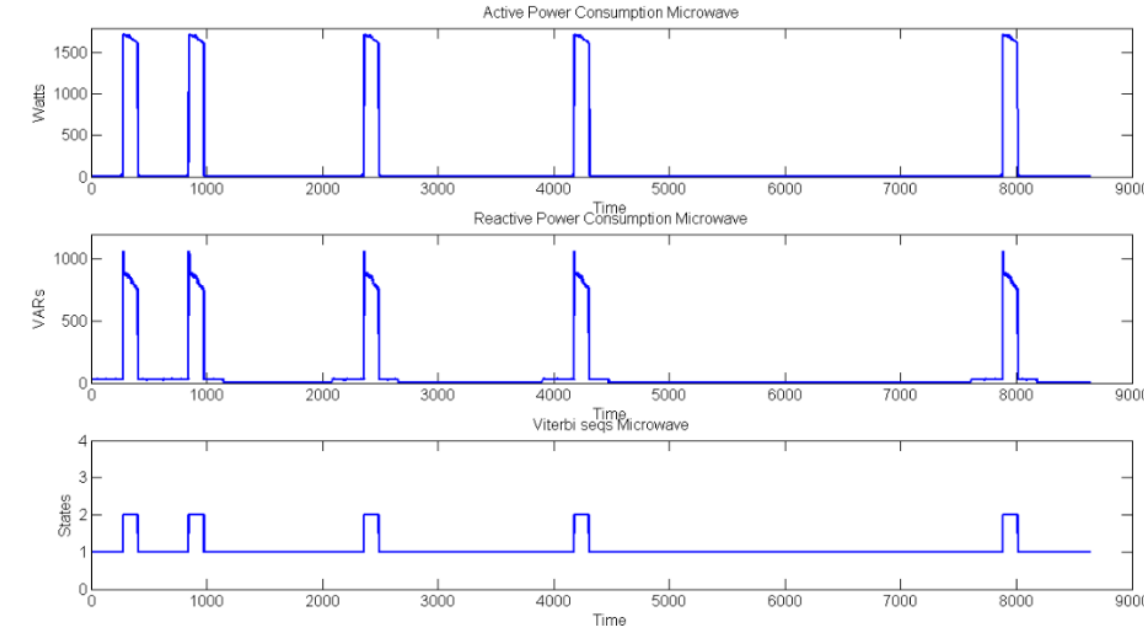

Figure 3-2 Active and Reactive power consumption of microwave with Viterbi sequence

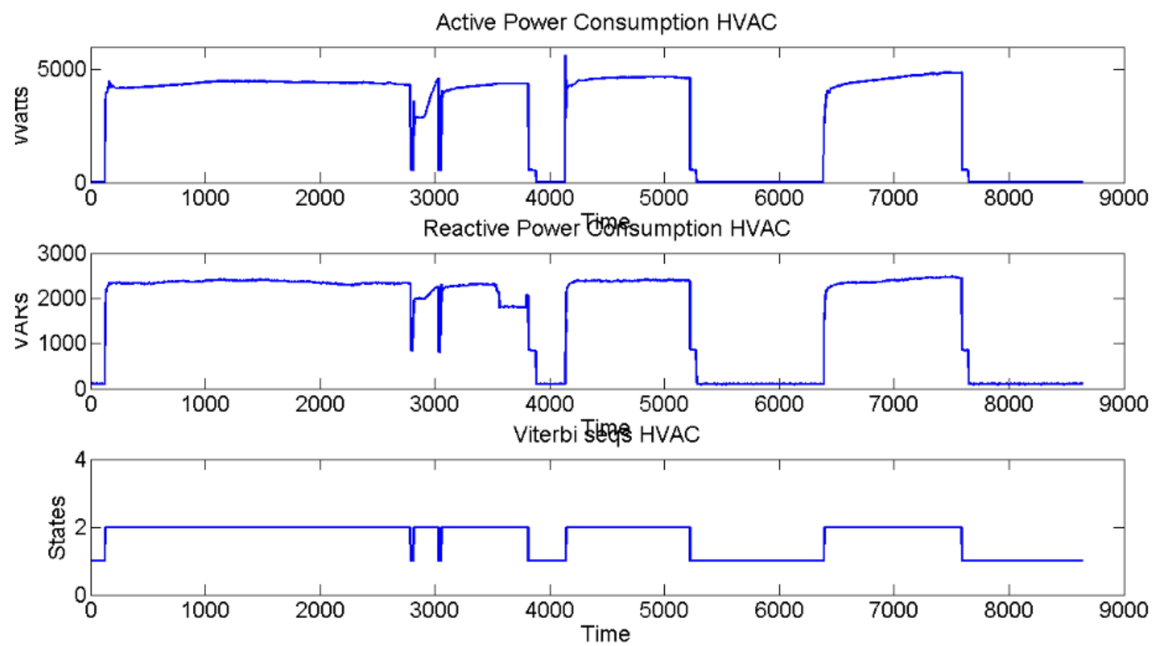

Figure 3-3 Active and Reactive power consumption of HVAC unit with Viterbi sequence

3.2 MODELING COMBINED LOAD HIDDEN MARKOV MODEL

After modeling individual appliance we move forward to build the combined Hidden Markov model. The likelihood of the combined observation sequence is P (O| λ') given the Hidden Markov model λ'=(A, φ_{active} $\varphi_{reactive}$, π). The parameters of the combined model are adjusted to maximize the likelihood of the combined observation sequence. Lastly the optimal state sequence is deduced by the Viterbi algorithm from the combined observation sequence and the model. The combined model is obtained by forming an observation matrix and a transition matrix which represents all the possible combination of the appliances. Kronecker operator is used to compute the combined observation and transition matrix. The combined transition matrix is obtained as,

$$A_{combined} = (((A_1 \otimes A_2) \otimes A_3) \ldots \otimes A_p) . \tag{14}$$

The devices are combined sequentially, and the order they are added to the model is important. $\boldsymbol{A}_{\text{combined}}$ is the combined transition matrix, where A_1, A2 through A_p where p is the number of appliance in the system

The continuous distributions of observations are converted into a discrete probability mass function which is represented in a matrix. This is done by choosing an appropriate bin size B_S The bins form an ordered partition of the range of possible power use indexed from 1 to z. The bin size is limited by physical constraints and also determines the size of the observation matrices, with maximum bin size being z.

The discrete element φ for device p is calculated by integrating the observation density function over the set of bins.

$$\varphi_{ij}^{(p)} = \int_{(j-1)Bs}^{(j)Bs} \varphi_i^{(p)}(O_t)dO_t,\ j = 1, 2...z \tag{15}$$

The integration over bins ensures that no bin contains a zero observation probability, which would result in incomplete training data if the observation matrix were taken from the sequence of binned observation. The methodology used for combining the observation matrix is explained in Appendix B. Elements with low probability may be neglected by setting a minimum probability threshold of, ϵ. ϵ is set to 10^{-9}. Once these low probability elements are eliminated, the rows of observation matrix are normalized such that they form a valid probability mass function. Our composite model consists of two observation matrices consisting of φ_{active} and $\varphi_{\text{reactive}}$. Both the observation matrices are computed using the same process.

The observation matrix for the combined system is produced by computing the Kronecker product of individual matrices and summing the columns corresponding to equal total observation. The sum results from the fact that power contribution from each device is additive. The computation of the Kronecker product is slow. Thus it is much easier to find the combined observation matrix by column. This process is repeated for p devices and is combined in the same order in which the transition matrices are combined. This has to be done only once.

3.3 STATE DISAGGREGATION

The composite model consisting of p devices has combined transition matrix ($A_{combined}$) and observation matrix (φ_{active}, $\varphi_{reactive}$). A sequence of observation O_{active} and $O_{reactive}$ is computed for the entire system. For a closed system where the entire system with different device is known, observation is given by,

$$O_{active} = \sum_{p=1}^{p} O_{active}^{p} \tag{16}$$

$$O_{reactive} = \sum_{p=1}^{p} O_{reactive}^{p} \tag{17}$$

where O_{active} and $O_{reactive}$ is unknown energy contribution of p devices. NILM helps us to find the best possible estimate of these contributions. The disaggregation process is done as explained in [19]. The first step for disaggregation is to determine the composite model sequence of state. The composite sequence $\hat{Q}$ obtained is the result of composite observation sequence based on both O_{active} and $O_{reactive}$.The composite sequence $\hat{Q}$ is a result of composite transition matrix $A_{combined}$, φ_{active} and $\varphi_{reactive}$. It shows the most likely behavior of all p devices considered as single system. Figure 3-4 and Figure 3-5 show the composite active and reactive observation sequence and the composite Viterbi sequence for the appliances in the system . The system of loads in Figure3-4 consists of oven, dryer, microwave and HVAC system. Each device had two states and hence the composite model consists of 2^p composite states as we see in the plot where p is the number of device is the system.

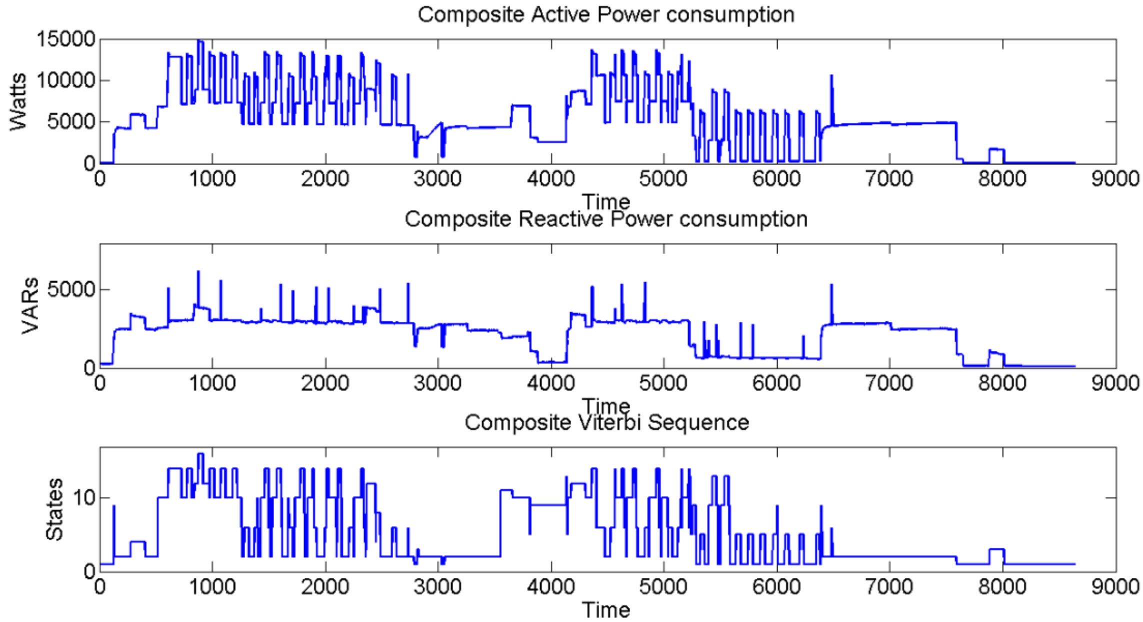

Figure-3-4 Composite Active and Reactive Power consumption of oven, dryer, microwave and HVAC along with composite Viterbi sequence of the system

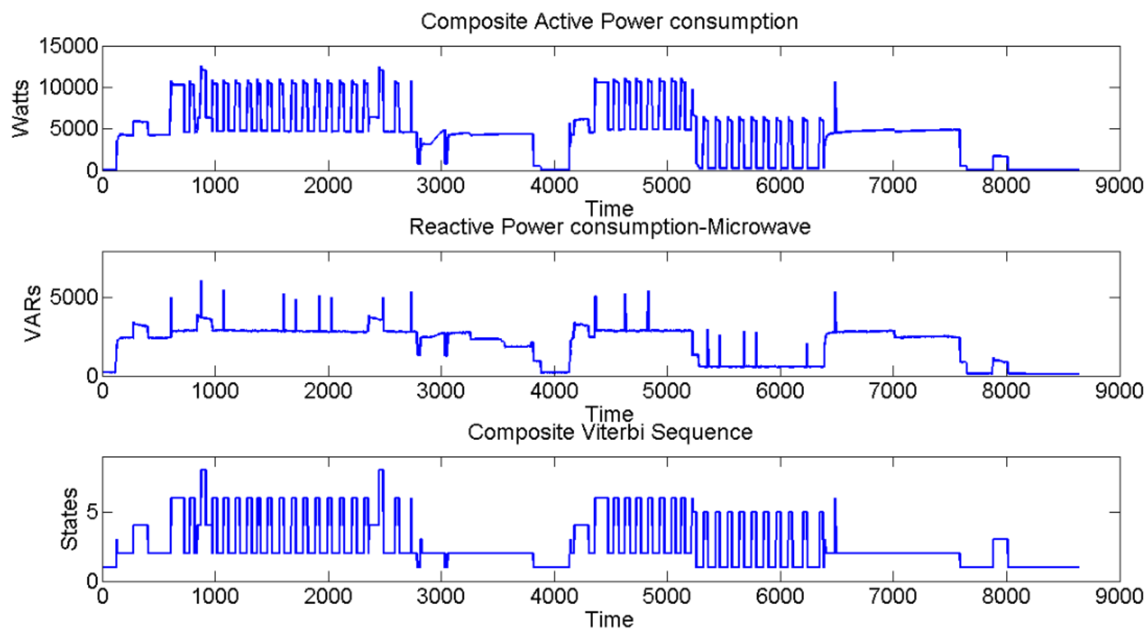

Figure. 3-5 Composite Active and Reactive Power consumption of dryer, microwave and HVAC along with composite Viterbi sequence of the system

Next step is to disaggregate the composite state sequence to find the most likely sequence of each individual device. Due to the use of Kronecker product during the construction of the composite model the states of the composite Viterbi path are interleaved. The disaggregation of individual model depends on the order the individual model and has been included in the composite model. From the set of *p* devices, let *Np* be the number of states in *p*th device, numbered in order of inclusion in (14). Then the generalized disaggregation can be expressed as (18)

$$\hat{Q}_t^{(p)} = \mathrm{mod}\left(ceil\left(\frac{\hat{Q}_t}{\prod_{j=p+1}^{P} N_j} \right) - 1, N_p \right) + 1 \tag{18}$$

Where $\hat{Q}_t^{(p)}$ is the Viterbi path for the *p*th device at instant *t*. Mod and ceil are the modulo and ceiling function respectively. Figure 3-6, Figure 3-7 and Figure 3-8 show the disaggregated appliances starting with oven, dryer, microwave and lastly HVAC. The Viterbi sequence of the disaggregated appliance closely resembles their power consumption. The accuracy of the predictions is measured in the later section.

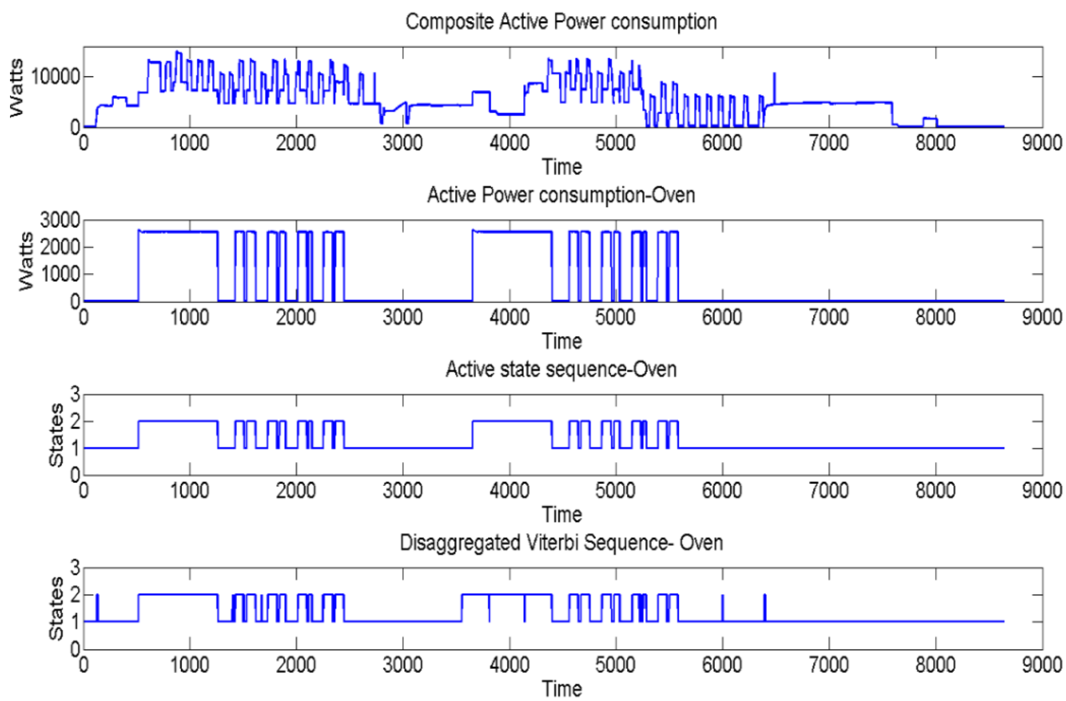

Figure 3-6 Active power consumption of oven, dryer, microwave, HVAC and disaggregated oven from the composite model

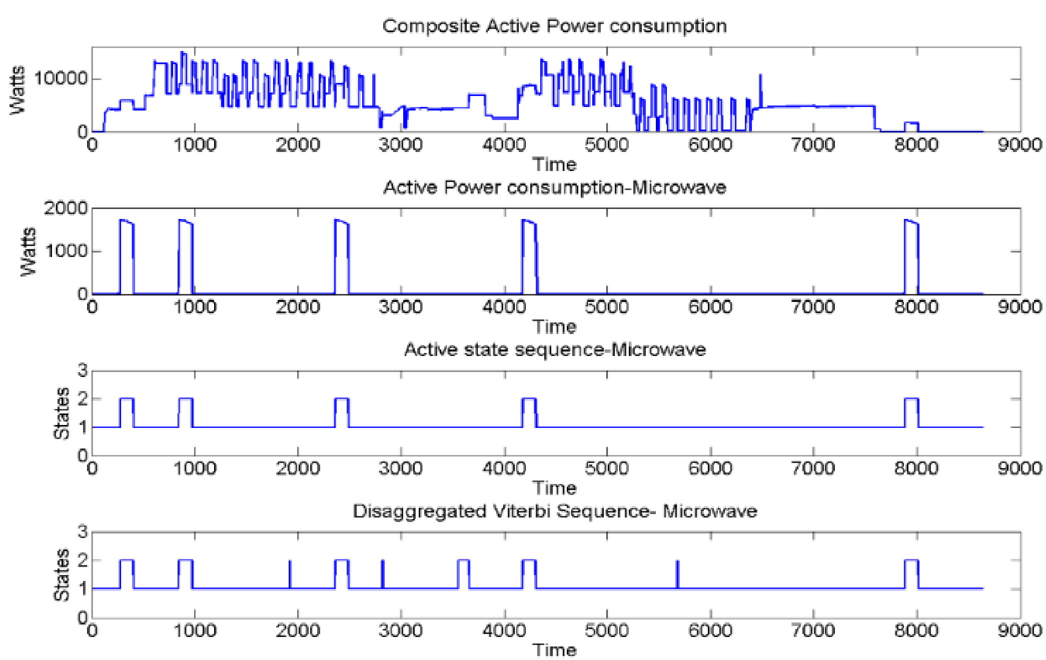

Figure 3-7 Active power consumption of oven, dryer, microwave, HVAC and disaggregated microwave from the composite model

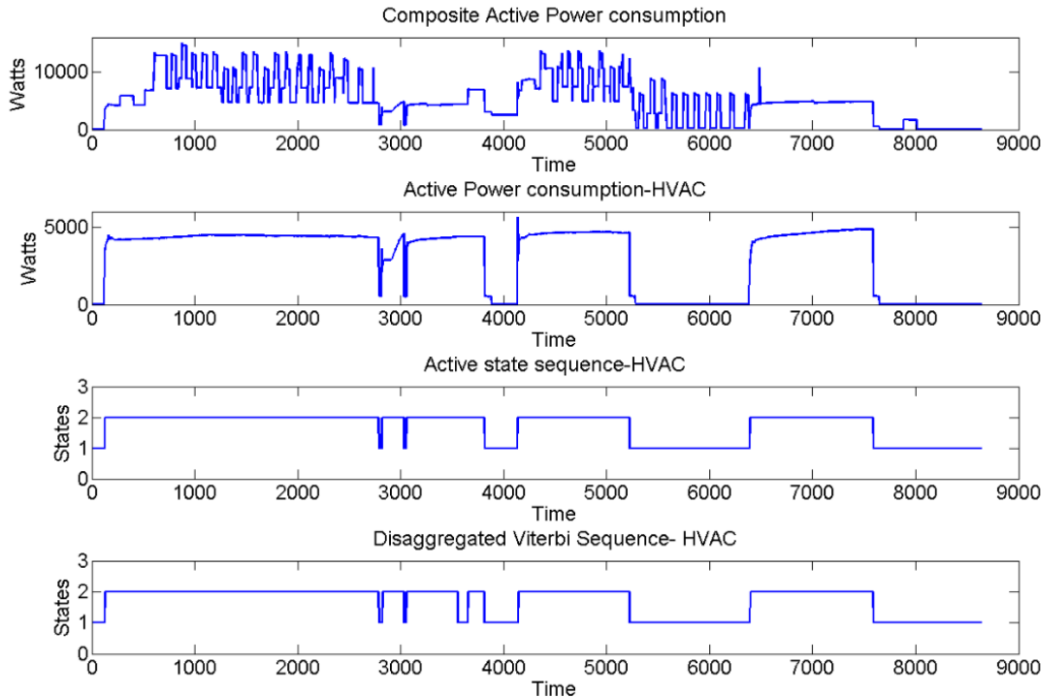

Figure 3-8 Active power consumption of oven, dryer, microwave, HVAC and disaggregated HVAC from the composite model

4 POWER ESTIMATION

Once the Viterbi sequences for individual appliances are computed, the next step is to predict the energy use for each device. The simplest way to approach is to use the best possible constant estimator. For this we can use the expected value of observation for a given state. [19]

$$\hat{O}_t^p = E[O_t^{(p)} | \mathrm{Q}_t^{(p)} = j] = \mu_j^{(p)} \tag{19}$$

The total energy use predicted for device *p* can be computed as

$$\hat{W}^{(p)} = T_S \sum_{t=1}^{T} \hat{O}_t^p \tag{20}$$

This method is useful for estimating cumulative energy use over the period of time. This is a rough approximation of the device behavior. The possible observation is limited to number of state defined in the model. Thus prediction of observation is constant in time when the state is not changing. Figures 4-1 and 4-2 show the actual active and reactive power consumption of oven and microwave along with their predicted active and reactive power.

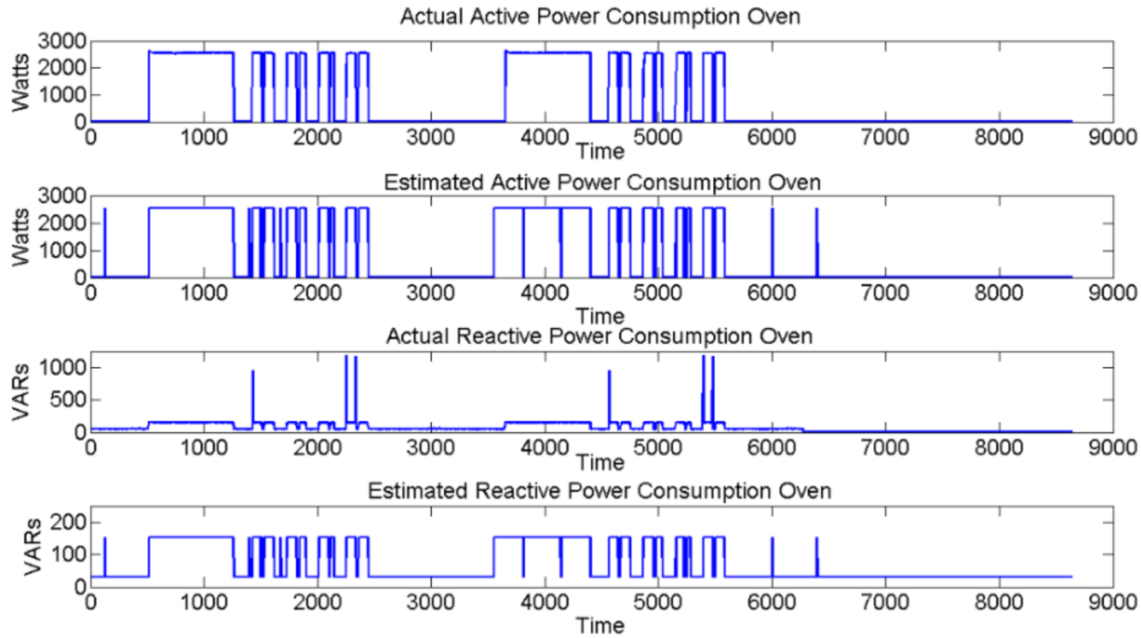

Figure 4-1 Predicated Energy use for oven

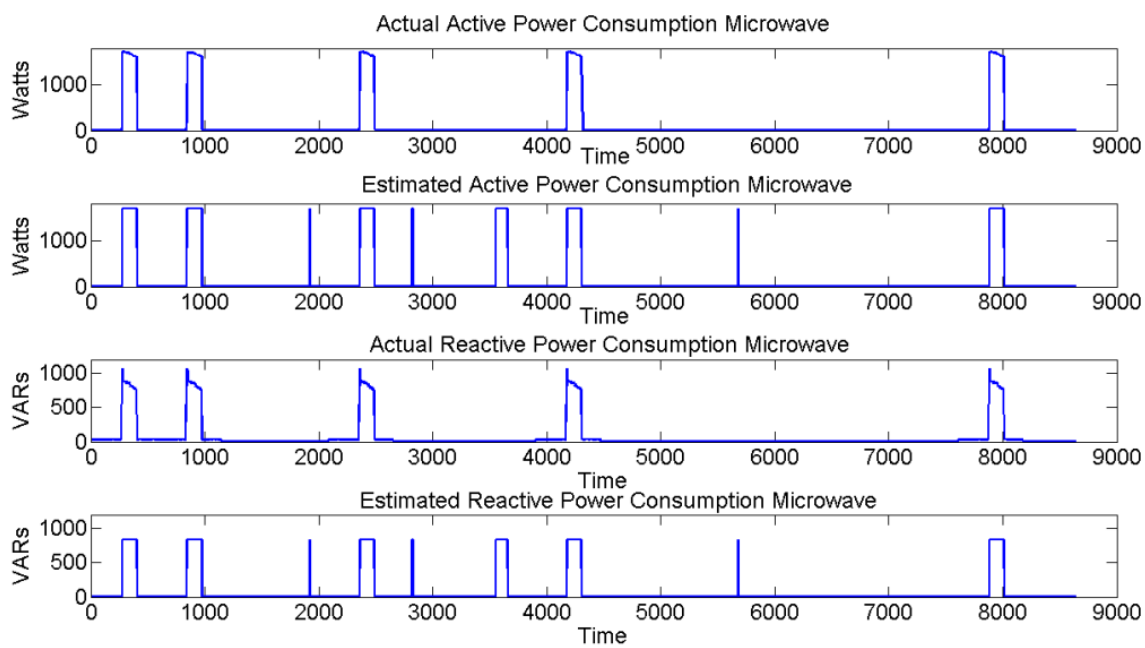

Figure 4-2 Predicated Energy use for microwave

5 EVALUATING THE PROPOSED METHOD

This section discusses the success rate of the proposed method the best state sequence using both active and reactive power consumption of an appliance. The performance metrics of interest are how closely the outputs of the system match the model's ground truth. The tests were carried out using the data which we used for building the model. The evaluating metrics used to measure the accuracy of the proposed method we calculated the correlation co-efficient, precision measure, recall measure and f-score for individual appliance as mentioned in [20]. The value of the correlation co-efficient and f-score test are compared against the results using just active power.

The proposed disaggregation method is evaluated by calculating the accuracy of the Viterbi path to the original state sequence of each model. The basic accuracy measure is defined as

$$Acc. = \frac{correct}{correct + incorrect} \tag{21}$$

The problem with this is the appliances which are 'OFF' for longer period of time will have greater accuracy thus we need to consider other parameters which can help us assess the accuracy of the prediction of states. It is also important to measure how accurately the NILM algorithm can predict which appliance is running at each state. F-scores are well suited for this task.

$$F = 2\frac{(precision)(recall)}{precision + recall} \tag{22}$$

$$precision = \frac{tp}{tp + fp} \qquad recall = \frac{tp}{tp + fn} \tag{23}$$

Where, precision is positive predictive values, recall is true positive rate, *tp* is true positive i.e. when correctly predicted that the appliance is ON, *fp* is false positive *fp* is false-positives (predicted appliance was ON but was OFF), and *fn* is false-negatives (appliance was ON but was predicted OFF). The measurement of *tp, fp, fn* are accumulations over a given experimental time period. The following table gives the tested results for the proposed method.

The table below shows the results for the method used to model appliances using only active power. The four appliances used for our model includes oven, microwave, dryer and HVAC. Comparing results from Table 5-1 and Table 5-2 show that the proposed method is more accurate. Figure 5-1 shows accuracy of the Viterbi sequence using proposed method.

Table 5-1 Results of the proposed method

Appliance	Correlation Co-eff	F-score	Precision	Recall
Oven	0.9642	0.9888	0.9976	0.9800
Dryer	0.9936	0.9989	1	0.9978
Microwave	0.9128	0.9928	0.9996	0.9860
HVAC	0.9675	0.9777	0.9567	0.9996

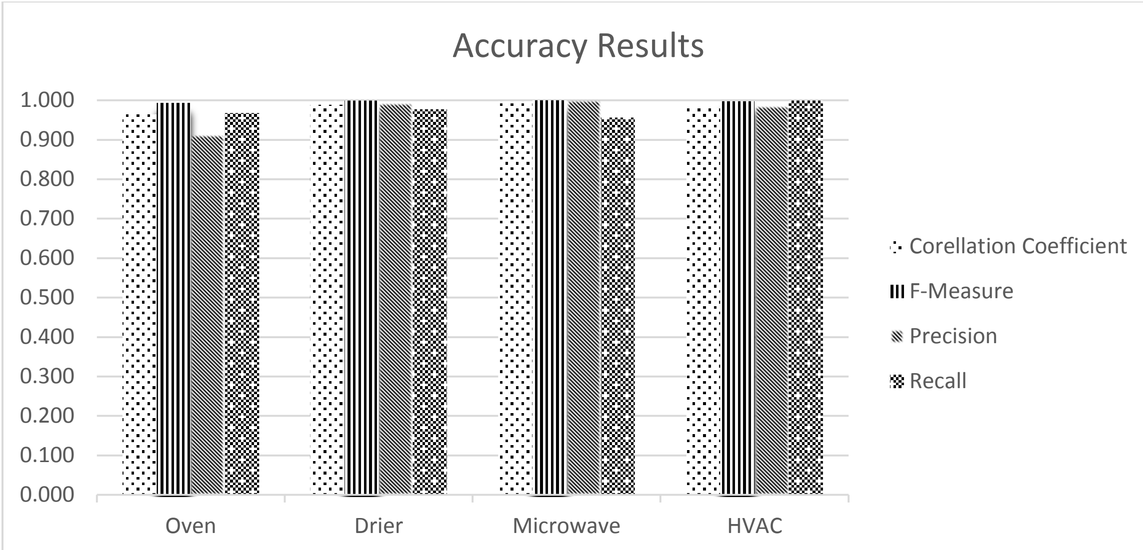

Figure 5-1 Bar graph showing the accuracy of the Viterbi Sequence with original state sequence for each device

Table 5-2 Result of model using only active power for oven, dryer, microwave and HVAC

Appliance	Correlation Co-eff	F-score	Precision	Recall
Oven	0.5157	0.9137	0.2475	0.5798
Dryer	0.7784	0.9839	0.8313	0.7093
Microwave	0.9349	0.9953	0.9692	0.5534
HVAC	0.6668	0.9729	0.7278	0.9876

Figure 5-2, Figure 5-3, Figure 5-4, Figure 5-5, show the accuracy of the proposed method compared to the method using only active power for Viterbi sequence prediction for oven, dryer, microwave and HVAC system respectively.

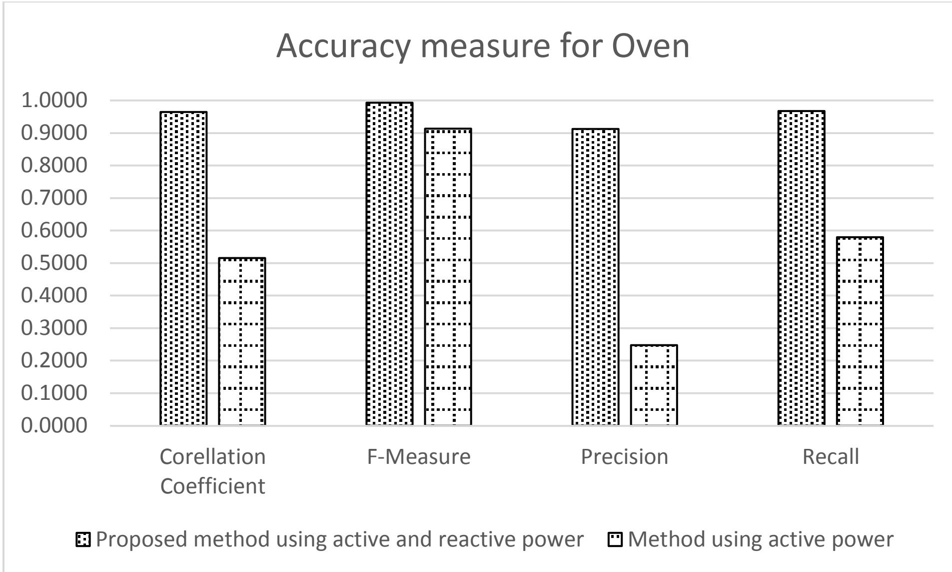

Figure 5-2 Result of proposed method using active and reactive power compared to previous method using only active power for oven

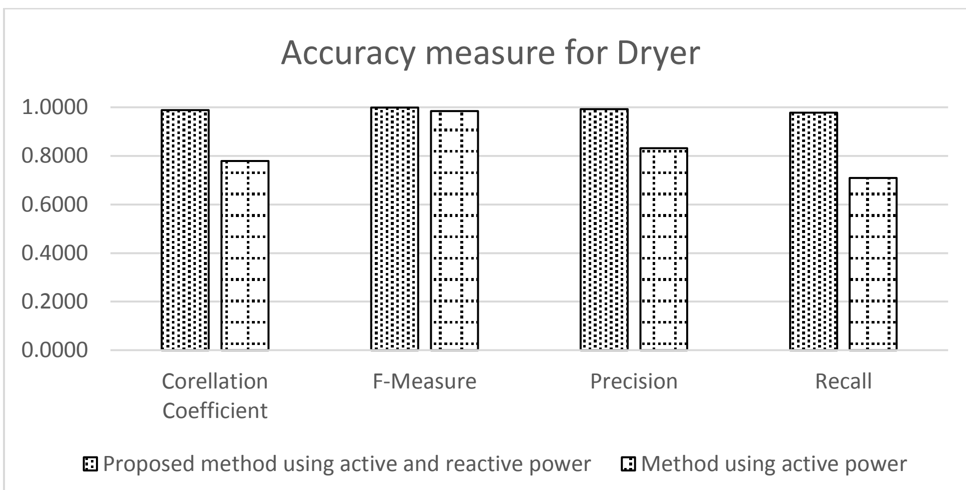

Figure 5-3 Result of proposed method using active and reactive power compared to previous method using only active power for dryer

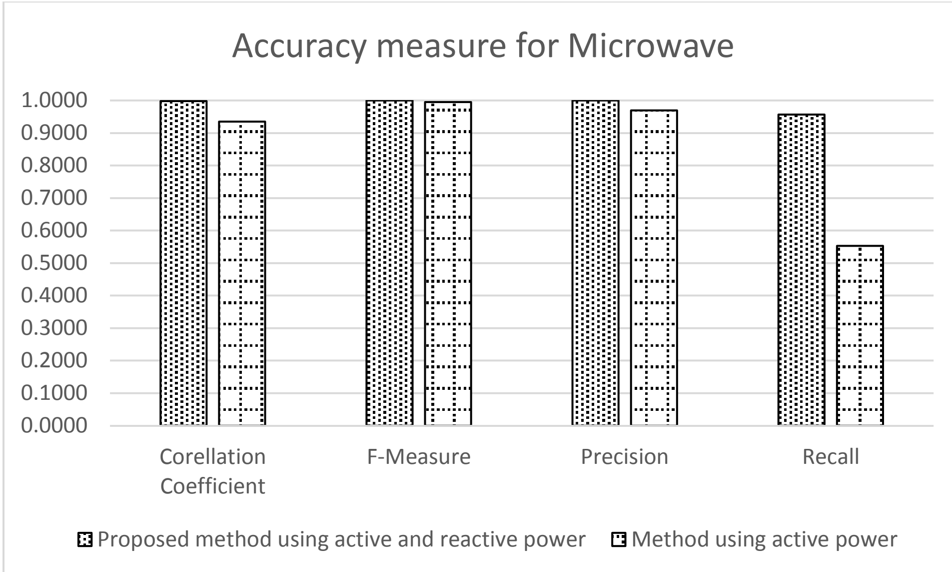

Figure 5-4 Result of proposed method using active and reactive power compared to previous method using only active power for microwave

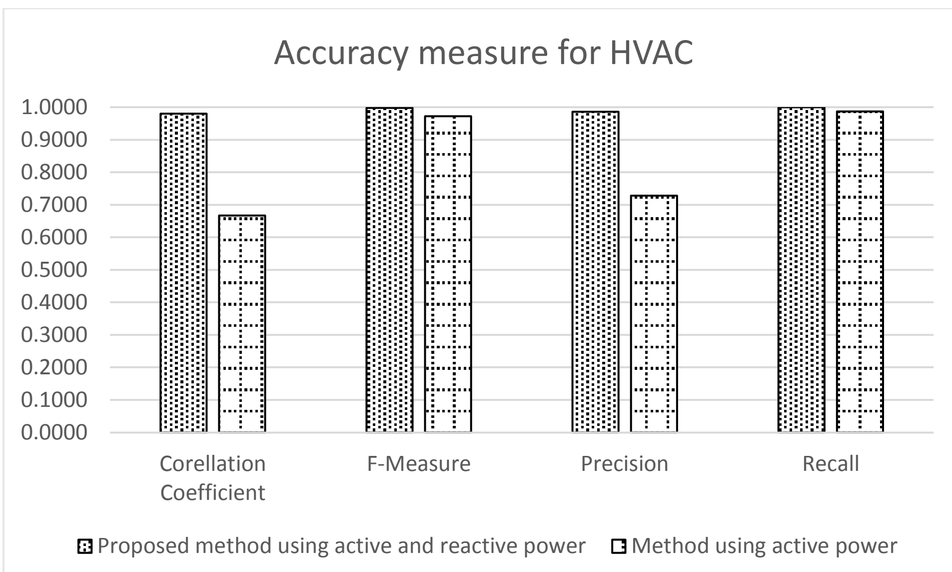

Figure 5-5 Result of proposed method using active and reactive power compared to previous method using only active power for HVAC

6 CONCLUSION

This research dealt with the fundamental goal of NILM problem, i.e. an appliance level disaggregation of house hold energy consumption data. Individual appliances are modeled using Hidden Markov Model using their active and reactive power measurement. A method to model the aggregated load and appliance disaggregation method was discussed. The proposed method using both active and reactive power was found to be more accurate compared to when appliances were modeled using only active power consumption data. The devices considered for this research had extensive device level data. The method show better performance when for the appliance whose observation distribution has large variance. This system only considers the steady state operation of appliances. Using both active and reactive power for the state estimation greatly reduces the predictive error.

7 FUTURE WORK

For our study we could only attain 4 devices with one particular model per appliance with valid dataset to work with. Further work could be done to attain more valid dataset and verify the robustness of the algorithm. Adding more models per appliance the composite model tends to be more complex and then using both active and reactive power observation might help better disaggregate the composite model. Appliance with more reactive power characteristics can be used for better state and power estimation.

Furthermore this work can be extended to use in systems using multiple voltage rails. For example small satellites use multiple voltage busses for their system and this work can be further used in such a system to compute multiple observation matrices with one transition matrix.

APPENDIX A

PSEUDO CODE FOR VITERBI ALGORITHM

This section contains the pseudo code for the Viterbi algorithm that has been used in this proposed method to find the state sequence of the appliances. Here 'm' is the number of state the in the composite model. The algorithm goes through each step of time through each state calculating the highest probability and storing it in an array. Once this is completed the path is back traced by taking the highest probability at each step of time. *OS* contains the best state sequence given the transition and probability matrix of a model. The log probability is being considered since the computation is much more efficient that multiplication. The speed and accuracy of the algorithm is much faster

% use Viterbi to calculate observation probability

% T: array of observations, length \`t\`

% S: array of states, length \`m\`

% O: observations, length \`n\`

% A(m, m): state transition probability distribution

% φ (m, n): observation probability distribution

$function\ viterbi\ (T,\ S,\ A, \varphi)$

$V\ =\ zeros(t,\ m)$

% store back-references to figure out the actual path taken to get there

$P\ =\ zeros(t,\ m)$

% iterate through each time step

$for\ i\ in\ 1:t$

% and consider each state

$for\ s\ in\ 1:m$

% get array of probabilities of having been in each previous step, multiplied by the probability of transitioning to the current state

$X = zeros(m)$

% to avoid multiple calls for max

$for\ x\ in\ 1:m$

$$X(x) = log(V(i-1, x)) + log(A(x, s))$$

end

end

$$V(i, s) = log\ (max(X)) + log(\varphi_{active}(s, T(i))) + log(\varphi_{reactive}(s, T(i)))$$

$P(i, s) = argmax(X)$

end

% build the output sequence by tracing the back pointers of the highest

% probabilities at each step

$OS = zeros(t)$

$OS(t) = P(t, argmax(V(t)))$

$for\ i\ in\ t-1:1$

$prepend(OS, P(i, argmax(V(i))))$

end

$return\ OS$

end

APPENDIX B

OBSERVATION MATRIX COMPUTATION FOR COMPOSITE MODEL

The following section explains how the composite observation matrix is computed. The observation matrix is converted into discrete probability mass function such that they can represented in matrix form. The observation are converted from continuous distribution to discrete representation by assuming an appropriate bin size for the application. The bins are indexed from 1 to k here in the algorithm. The size of bins determines the size of individual device and in extension, the size of the composite matrix. The discrete elements are computed as shown earlier by Eq. [15]. The composite model is found by computing the Kronecker product of the column of individual observation matrix and summing the columns that corresponds to equal total observations. First we start by initializing the active and reactive observation sequence for the first and second device in the same order the composite transition matrix was computed. Variable *z* and *x* keeps track of the column corresponding to equal total observation. The calculated observation matrix is stored in phi_cal_active and phi_cal_reactive. The observation matrix for the next model is taken and the process is repeated.

```
% initializing the observation matrix for the first appliance
AO_Active = Model [15].O_active;
AO_Reactive= Model [15].O_reactive;
for i in 2:length(Model)

% initializing the observation matrix for the next available device
  BO_Active = Model(i).O_active;
  BO_Reactive= Modeli).O_reactive;
```

```
for k=1:(size(AO_Active,2)+size(BO_Active,2)-1)
    if z==x && z+x<=2
% Kronecker product of the first column of first device and first column of second device
phi_cal_Active(:,s)=kron(AO_Active (:,z),BO_Active (:,x));
phi_cal_Reactive(:,s)=kron(AO_Reactive(:,z),BO_Reactive(:,x));
        s=s+1;
        z=1;
        x=0;
    else
% Addition of the column with equal total observation
        p=k;
        if p<=size(BO_Active,2)
            z=1;x=p;
            d=z+x;
            for q=1:p
                if z+x==d
% Addition of the columns with equal total observation
n_active=kron(AO_Active(:,z),BO_Active(:,x));
m_active=n_active+m_active; n_reactive=kron(AO_Reactive(:,z),BO_Reactive(:,x));
                m_reactive=n_reactive+m_reactive;
                    z=z+1;
                    x=x-1;
                    if x<1 && z>=p
```

```
            break
          end

        end
      end

      phi_cal_Active(:,s)=m_active;
      phi_cal_Reactive(:,s)=m_reactive;
      s=s+1;
    else

      x=size(BO_Active,2);z=p-x+1;
      d=z+x;
     for q=1:p
       if z+x==d
        n_active=kron(AO_Active (:,z),BO_Active(:,x));
% Addition of the columns with equal total observation
m_active=n_active+m_active;
n_reactive=kron(AO_Reactive(:,z),BO_Reactive(:,x));
m_reactive=n_reactive+m_reactive;
          z=z+1;
          x=x-1;
          if x<1||z>size(AO_Active,2)
```

```
                break
              end
            end

          end
          phi_cal_Active(:,s)=m_active;
          phi_cal_Reactive(:,s)=m_reactive;
          s=s+1;
        end
      end

      m_active=zeros(size(AO_Active,1)*size(BO_Active,1),1);
      m_reactive=zeros(size(AO_Active,1)*size(BO_Active,1),1);

    end
%Saving the composite matrix of first two device to be used in computing the next devices
    AO_Active =phi_cal_Active;
    AO_Reactive =phi_cal_Reactive;
    s=1;
    z=1;x=1;
end
```

REFERENCES

[1] G. W. Hart, "Nonintrusive appliance load monitoring," *Proceedings of the IEEE,* vol. 80, pp. 1870-1891, 1992.

[2] S. Makonin, F. Popowich, I. V. Baji, x, B. Gill, and L. Bartram, "Exploiting HMM Sparsity to Perform Online Real-Time Nonintrusive Load Monitoring," *IEEE Transactions on Smart Grid,* vol. PP, pp. 1-11, 2015.

[3] L. Yi-Sheng, C. Yung-Chi, T. Shiao-Li, and T. Tzung-Cheng, "A novel search scheme for nonintrusive load monitoring systems," in *Industrial Technology (ICIT), 2012 IEEE International Conference on*, 2012, pp. 102-107.

[4] J. M. Andreoli, "Learning energy consumption profiles from data," in *Computational Intelligence and Data Mining (CIDM), 2014 IEEE Symposium on*, 2014, pp. 463-470.

[5] T. Zia, D. Bruckner, and A. Zaidi, "A hidden Markov model based procedure for identifying household electric loads," in *IECON 2011 - 37th Annual Conference on IEEE Industrial Electronics Society*, 2011, pp. 3218-3223.

[6] R. Streubel and B. Yang, "Identification of electrical appliances via analysis of power consumption," in *2012 47th International Universities Power Engineering Conference (UPEC)*, 2012, pp. 1-6.

[7] P. Ferrez and P. Roduit, "Non-intrusive appliance load curve disaggregation for service development," in *Energy Conference (ENERGYCON), 2014 IEEE International*, 2014, pp. 813-820.

[8] M. S. Tsai and Y. H. Lin, "Development of a non-intrusive monitoring technique for appliance' identification in electricity energy management," in *Advanced Power System Automation and Protection (APAP), 2011 International Conference on*, 2011, pp. 108-113.

[9] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," *Proceedings of the IEEE,* vol. 77, pp. 257-286, 1989.

[10] J. Liao, G. Elafoudi, L. Stankovic, and V. Stankovic, "Non-intrusive appliance load monitoring using low-resolution smart meter data," in *Smart Grid Communications (SmartGridComm), 2014 IEEE International Conference on*, 2014, pp. 535-540.

[11] T. Brants, "Estimating Markov model structures," in *Spoken Language, 1996. ICSLP 96. Proceedings., Fourth International Conference on*, 1996, pp. 893-896 vol.2.

[12] R. Jia, Y. Gao, and C. J. Spanos, "A fully unsupervised non-intrusive load monitoring framework," in *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, 2015, pp. 872-878.

[13] D. Egarter and W. Elmenreich, "Autonomous load disaggregation approach based on active power measurements," in *Pervasive Computing and Communication Workshops (PerCom Workshops), 2015 IEEE International Conference on*, 2015, pp. 293-298.

[14] M. Baranski and J. Voss, "Detecting patterns of appliances from total load data using a dynamic programming approach," in *Data Mining, 2004. ICDM '04. Fourth IEEE International Conference on*, 2004, pp. 327-330.

[15] Y. F. Wong, Y. Ahmet, x015E, ekercio, x011F, lu, *et al.*, "Recent approaches to non-intrusive load monitoring techniques in residential settings," in *Computational Intelligence Applications In Smart Grid (CIASG), 2013 IEEE Symposium on*, 2013, pp. 73-79.

[16] Z. Ghahramani, "An introduction to hidden Markov models and bayesian networks," *Int. J. Pattern Recognition and Artificial Intell.*, vol. 15, pp. 9–42, June 2001.

[17] I. Abubakar, S. N. Khalid, M. W. Mustafa, H. Shareef, and M. Mustapha, "An overview of Non-intrusive load monitoring methodologies," in *2015 IEEE Conference on Energy Conversion (CENCON)*, 2015, pp. 54-59.

[18] J. A. Mueller, A. Sankara, J. W. Kimball, and B. McMillin, "Hidden Markov models for nonintrusive appliance load monitoring," in *North American Power Symposium (NAPS), 2014*, 2014, pp. 1-6.

[19] J. A. Mueller. a. J. W. Kimball, "An accurate method of energy use prediction for systems with known composition," *Proc. 3rd. Int. Workshop on Nonintrusive Load Monitoring*, May 2016.

[20] S. Makonin and F. Popowich, "Nonintrusive load monitoring (NILM) performance evaluation," *Energy Efficiency*, vol. 8, pp. 809-814, 2015.

VITA

Paulomi Nandy was born in Kolkata, India. In June 2012 she received her Bachelor in Electrical Engineering from Priyadarshini College of Engineering in Nagpur, India. In December 2016, she received her Master's degree in Electrical Engineering from Missouri University of Science and Technology, Rolla, USA.